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A MULTI-CHANNEL VITAL SIGNAL PROCESSING METHOD FOR DETECTION AND VALIDATION OF RESPIRATION DISORDERS

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Abstract

This paper presents a method for the detection and reliable validation of respiration disorder by using multi-channel vital signal processing. The main scope is the automated detection and analysis of a very common respiration disorder, the apnea syndrome. Apnea diagnostics requires long-term multi-channel vital signal recording, called polygraphy. Although various methods already exist for the computer-aided analysis of polygrams, only some of them offer precise apnea typing (i.e. distinguish between central vs. obstructive episodes) and event validation. The system introduced in this paper processes respiration, heart rate, blood pressure, and blood oxygen saturation signals. The episodes of apnea are classified, typed and validated over an 80% success rate compared to reference annotations made by medical experts. The detected episodes are validated by the rule-based classification of the characteristic changes in the cardiovascular signals caused by episodes of apnea.

Keywords: vital signal processing, apnea detection, multi-channel signal, event validation.

1. Introduction

The measurement and monitoring of respiration is important in many clinical circumstances. Respiration is the most important modulator of heart rate (HR), the source of short term heart rate variability (HRV), and directly influences the level of blood oxygen saturation (SaO_2). The analysis of respiration induced HRV and SaO_2 changes give important insight in the current status of the cardiorespiratory system and autonomic nervous activities [1, 2]. Respiration is therefore an important parameter in intensive care monitoring, and gradual alterations in respiration rate are often reason for treatment changes.

The full and the partial cessation of breathing over a given period of time, called apnea and hypopnea, are the most important short term respiration disorders. Apnea events can cause the oscillation of the cardioresiratory signals which can be dangerous or even life threatening for heamodynamical instable patients at the intensive care units.

Apnea is also a quite common phenomena during sleep, especially in the elderly male population of industrially developed lands, where over 30% of the population is affected.

The origin of apnea can be central which is caused by the abnormalities of the central motoneural system, or obstructive which is induced by the local obstruction or structural deformation of the upper airways. Each episode of apnea causes the fall of blood oxygen level which is followed by increased sympathetic nervous activity, i.e. increased heart rate and blood pressure.

Clinical relevance has periods of apnea over 10 seconds and more than 5 times per hour [1]. The periodic and long-term presence of apnea can lead to the evolution of various complications with severe consequences without treatment, such as hypertension, stroke, coronary heart disease, diabetes, obesity, and decline in mental state.

Several methods exist to measure respiration indirectly through thorax or abdomen movements or electrical impedance variances [3]. The gold standard, however, is the direct measurement of air flow in the mouth and nose, using temperature measurement of the in- and out-flowing air. Alteration of HR and the desaturation episodes in the SaO_2 signal provide supportive evidence for the event validation [4].

Episodes of central apnea (CA) and obstructive apnea (OA) can be distinguished by analysing the respiration movements (at the thorax and/or at the abdomen) and the air flow. In the case of CA, the movements are ceased or have only very low amplitudes compared to normal breathing. During an OA the obstruction of airways leads to increased respiratory movements which try to overwhelm the obstruction.

The computer support is as important in the case of real-time apnea detection as it is in the case of off-line evaluation and processing of long-term polygraph records.

Numerous methods exist for the detection of presence and severity of apnea [5, 6, 7]. Most of them use time domain algorithms which examine the amplitude and frequency of the respiration. These tools can detect episodes of apnea at 80-90% precision. The detection of episodes of hypopnea (reduced breathing) and the automated distinction between central and obstructive events (i.e. apnea typing) is far not so efficient.

The author made some preliminary research in the field of respiration signal processing [8, 9]. This paper presents new results and observes the problem of apnea detection from a new and unique point of view.

The method presented in this paper processes multi-channel polygraph records in order to provide a more reliable and exact detection and validation of episodes of apnea, their type and severity.

2. Methods

2.1. Signal Records

The multi-channel signal records of the PhysioNet database were used in this study [10]. Following signal channels were selected or derived from the records of the Polysomnography Database for further signal processing: nasal air flow (NAF), thoracic or abdominal excursion (THX), HR (derived from the RR-distances in the measured electrocardiograms), systolic blood pressure (SBP), and SaO_2. The signals were originally sampled at 250 Hz.

The following *Fig.* 1. shows a typical record section which contains severe episodes of obstructive and central apnea. The respiration signals are displayed in normalized units [nu].

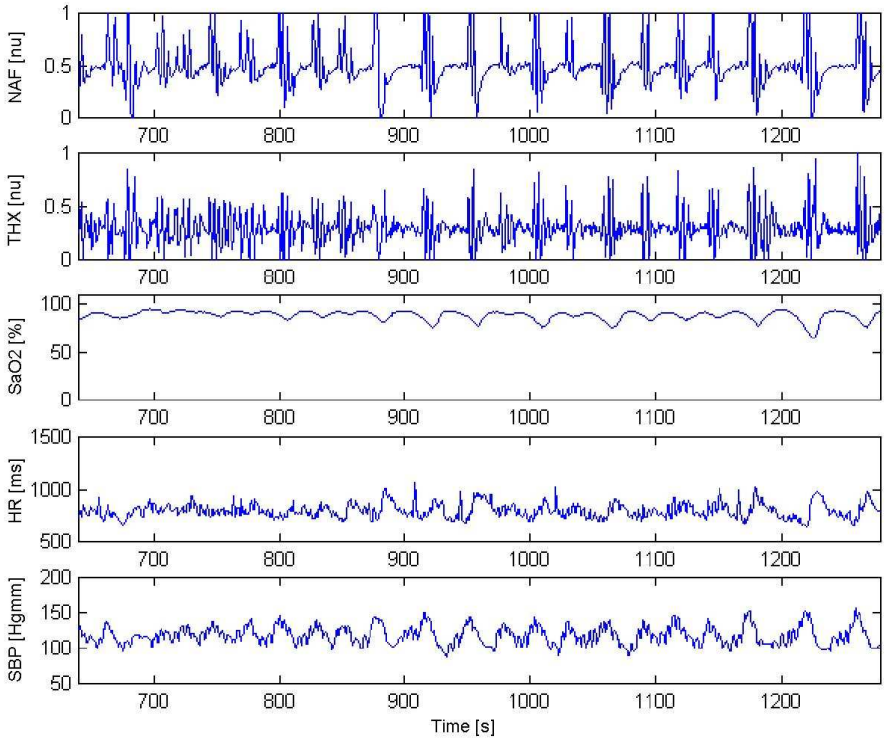

Fig. 1. Excerpt of a polygraph containing episodes of apnea

Altogether 6 sections of 4 different records were selected from the database having an average length of 1 hour. The sections contained 24 to 64 episodes of apnea (on the average 38 events). An expert of respiratory medicine annotated the episodes of apnea and hypopnea in the records.

Table 1. Episodes of respiration disorder and their severity in the record sections used

Record section	# of episodes		Low severity	Medium severity	High severity
Apnea (A) or hypopnea (H)	A	H	A	A	A
S1	27	41	11	14	2
S2	33	53	21	7	5
S3	64	91	11	23	30
S4	31	8	6	22	3
S5	45	19	14	19	12
S6	29	18	4	24	1

In the case of episodes of apnea, the location, the type and the severity (low, medium or high impact on cardiovascular system) were annotated. At the episodes of hypopnea only the locations of the events were annotated. This annotation information was used later as reference data. The total number of episodes and their severity is shown in *Table 1*.

2.2. *Apnea Detection and Typing*

The apnea and hypopnea detection and typing (central vs. obstructive events) is based on the processing of the NAF and the THX signals (see *Fig.* 2). The cardiovascular signals (HR, SBP and SaO_2) contained in the polygraph records were not incorporated in the apnea detection, but later in the validation process. The reason for this is that apnea generated changes in these signals are delayed by many seconds with a characteristic strongly specific to the actual haemodynamic state of the patient.

For the detection and classification of episodes of apnea and hypopnea a neural-network-based method was used as described in [8].

Both the THX and NAF signals were baseline corrected, normalized and decimated at a sampling rate of 25 Hz prior to further processing by a signal conditioning and normalizing unit (SCN).

An instantaneous respiration amplitude (IRA) and an instantaneous respiration interval (IRI) signal were derived from the normalized NAF signal as detailed in [8]. The IRA and IRI signals were normalized and spanned over the continuous time (see *Fig.* 3).

The respiration patterns in the time series can be determined by an appropriate classification time window which is stepped over the signal. According to the medical definition of apnea, the length of the window should be at least 10 seconds in order to detect apnea within a single time window. The optimal length of the clas-

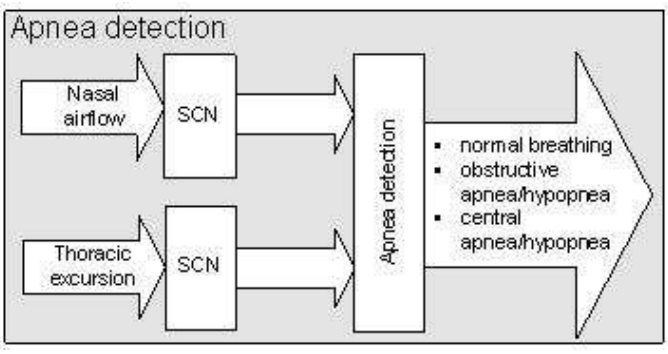

Fig. 2. Block diagram of the apnea detection

sification time window was empirically determined (16 seconds). The narrowing of the window would result in instable classification; the widening of the window would harden the network training and reduce the classification performance (see *Fig.* 4).

A feed-forward artificial neural network with two hidden layers (6 and 4 neurons per layer) was used for the classification of the derived respiration time series IRA and IRI. To keep the processing time at a reasonable size, the input signal of the network was decimated by a factor of 10 prior to classification. The goal of the classification was to determine, whether the respiration signal in the selected time window is normal breathing (N), an episode of hypopnea (H) or an episode of apnea (A). The network was implemented in Matlab, using the Neural Network Toolbox [11]. For the purpose of network training 60 NAF fragments were selected from 9 different polygraph records, each with the length of one time window (20 pieces of N, H and A fragments, each consisting of 25 sample points). The excerpts were taken both from the original and the derived IRA and IRI signals. The total number of training patterns was therefore 540 (60 patterns from each of the 9 selected training records).

The two network outputs were chosen as binary values, coding the respiration patterns corresponding to the actual input training pattern (N, H, A and X - unknown). Both the hidden and the output units had sigmoid-type activation functions and the ANN was trained by the back-propagation algorithm with gradient descent and momentum. The targeted mean squared error (MSE) was 10^{-3} which could be reached in less than 1000 training epochs.

The next step is the typing of the detected episodes of apnea, i.e. the distinction between central and obstructive events. Episodes of hypopnea were not required to be typed since hypopnea is related to obstructive events. The typing was based on the simple physiological fact that in the case of central apnea both the THX and the NAF signals are almost steady. In the case of an obstructive apnea only the NAF signal is steady, but thoracic movements are still present which try to overwhelm the obstructed upper airways. For this purpose, the IRA signals derived from the NAF

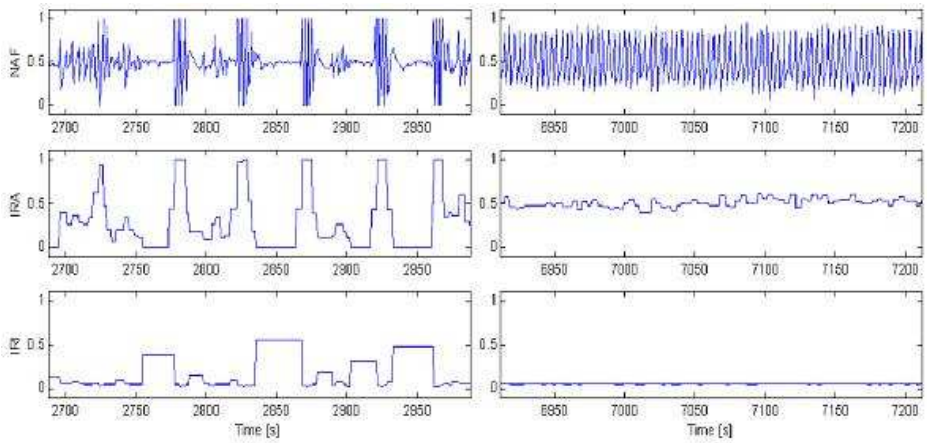

Fig. 3. Nasal air flow and the derived IRA and IRI signals at episodes of apnea (plots left) and in the case of normal breathing (plots right)

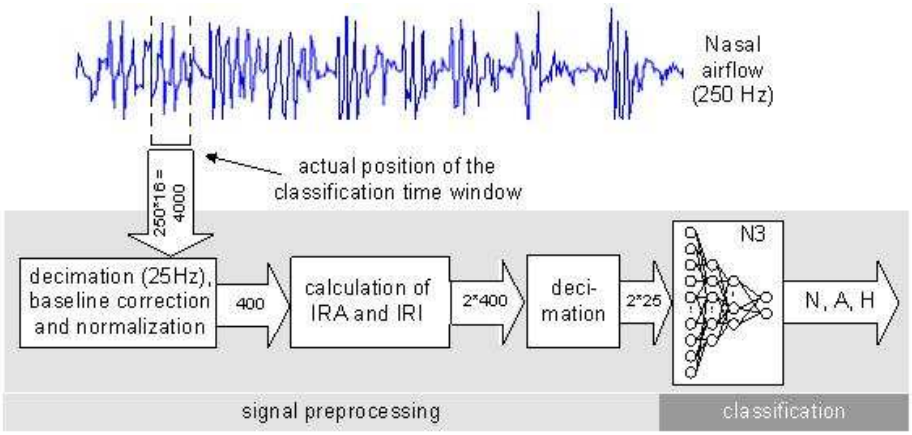

Fig. 4. Block diagram of apnea and hypopnea detection using neural-network-based pattern recognition

and THX were used. The A_x average value of the IRA derived from the signal x was regarded in the time window belonging to the apnea detected. The type of apnea was determined by comparing the A_x values to an N_x nominal value, measured during normal breathing. *Table* 2 shows the rules of apnea typing.

Table 2. The rules of apnea typing

Episode type	A_{NAF} in the time window		A_{THX} in the time window
Central apnea	IF $A_{NAF} < 0.1\, N_{NAF}$	AND	$A_{THX} < 0.1\, N_{THX}$
Obstructive apnea	IF $A_{NAF} < 0.2\, N_{NAF}$	AND	$0.4N_{THX} < A_{THX} < 1.5\, N_{THX}$
Central hypopnea	IF $0.3N_{NAF} < A_{NAF} < 0.6\, N_{NAF}$	AND	$A_{THX} < 0.3\, N_{THX}$
Obstructive hypopnea	IF $0.3N_{NAF} < A_{NAF} < 0.6\, N_{NAF}$	AND	$0.4N_{THX} < A_{THX} < 1.5\, N_{THX}$

2.3. Apnea Validation and Risk Analysis

According to medical practice, the validation and the risk determination of episodes of apneas are based on the analysis of the induced cardiovascular changes. For example, *Fig.* 1 shows an excerpt of a polygram containing severe episodes of apnea. The lack of breathing causes accelerated HRV and increasing SBP and decreasing SaO_2 values. After the breathing returns, the cardiovascular signals return into their normal range. As mentioned before, these cardiovascular changes are delayed by several seconds from the onset and offset of the episodes of apnea. This delay depends on the actual haemodynamic status of the patient, but according to medical practice, it lies between 5 to 30 seconds [1].

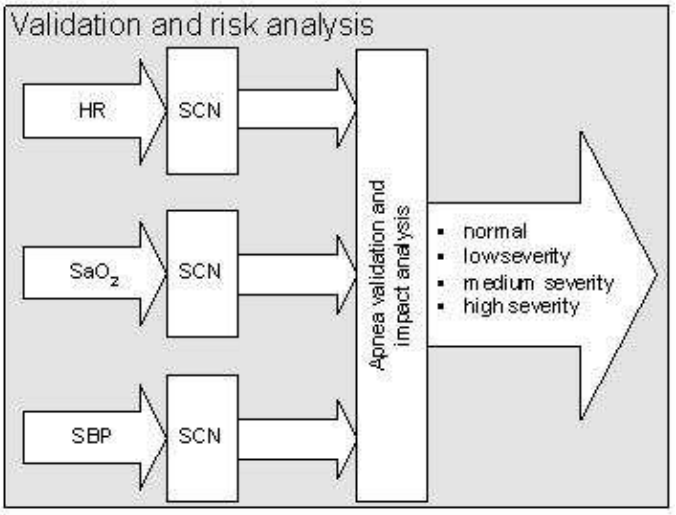

Fig. 5. Block diagram of the apnea validation

The HR, SBP and SaO2 signals were regarded at the apnea validation and at the determination of apnea's impact on cardiovascular changes, i.e. the determination of apnea's severity. The following table shows the rules of apnea validation and

risk analysis. The realized system validated each previously detected episodes of apnea by regarding the r_x relative magnitude change of the x vital signal over two consecutive time windows (32 seconds). If the relative change of any of the HR, SBP and SaO_2 signals fulfils a stricter severity criterion, the episode of apnea was automatically classified into the higher severity (e.g. the apnea has a medium severity if the HR acceleration in the two consecutive time windows around the detected apnea is higher than 20%, even if the relative change of the SBP and SaO_2 signals is below 5%). If the result of the validation was the severity category "None", the detected apnea was discarded (i.e. false detection).

Table 3. The rules of apnea validation

Severity	HR	SBP	SaO_2
None	$r_{HR} < 10\%$	$r_{SBP} < 8\%$	$r_{SaO2} < 5\%$
Low	$10\% < \mathrm{r}_{HR} < 20\%$	$8\% < \mathrm{ra}_{SBP} < 15\%$	$5\% < \mathrm{r}_{SaO2} < 10\%$
Medium	$20\% < \mathrm{r}_{HR} < 40\%$	$15\% < \mathrm{r}_{SBP} < 25\%$	$10\% < \mathrm{r}_{SaO2} < 15\%$
High	$r_{HR} > 40\%$	$r_{SBP} > 25\%$	$r_{SaO2} > 20\%$

Episodes of hypopnea were not validated because these events are often followed by an immediate apnea. Therefore the exact localization of the impact on the cardiovascular signals was not viable. However further study is needed for a feasible method on the resolution of this problem.

3. Results

The presented methods were implemented in Matlab. The neural network was realized by using the Neural Network Toolbox [11]. The patterns used at the training of the neural network originated from a former study and were not contained in the selected signal sections.

The specificity of the detection was measured by comparing the number of detected episodes with the annotations of the medical expert allowing a maximum time shift of one time window. Each detected apnea was typed and validated by using the methods described above. The number of correct detections, typing, and validations in per cents (i.e. the specificity measures) are shown in *Fig.* 5. The proportion of false detections (validation result controversial to the detected event) was below 5% at each of the records, therefore measures of selectivity were not displayed.

Table 4. Specificity of apnea detection, typing and validation

Record section	Detection		Typing of detected episodes	Validation of detected episodes
Apnea (A) or hypopnea (H)	A	H	A	A
S1	89%	84%	79%	88%
S2	86%	82%	78%	84%
S3	91%	88%	75%	93%
S4	88%	79%	79%	82%
S5	93%	84%	81%	87%
S6	90%	81%	80%	79%
Average	89%	83%	79%	85%

4. Discussion and Conclusions

Computer-aided vital signal processing became an essential tool of clinical diagnostics. The system presented in this paper provided the automated detection, typing and validation of episodes of apnea. The neural-network-based event detection is a common technique in vital signal processing [12]. The rule-based typing and validation is a well-known classification method, also at the analysis of respiration signals [13]. The main novelty of the presented system is the combination of the various processing methods in order to achieve better and more robust performance.

The preprocessing of the original respiration signals (NAF and THX) allowed the production of signals which are more suitable for neural-network-based event detection and for proper apnea typing. The derived IRA and IRI signals can represent the whole breathing process in a way which is adequately characteristic for the detection of respiration dynamics patterns. The derived signals are robust against sensor and patient-specific details of the original waveform. The detection of apnea and hypopnea was based only on the signals derived from the NAF. The use of the IRA from an additional respiration signal (THX) was essential in the typing of apnea. The simple rule-based methods used at apnea typing and apnea validation provided a clinically acceptable specificity of typing and validation.

The overall performance of the system is a promising result. The moderate computational power required by the method allows the implementation in portable devices.

The presented methods are capable of both off-line and on-line signal processing; therefore they can be applied in a broad range of medical diagnostics.

Although the presented system is suitable for robust detection, typing and validation of apnea, a comprehensive clinical validation study is still needed.

5. Acknowledgement

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